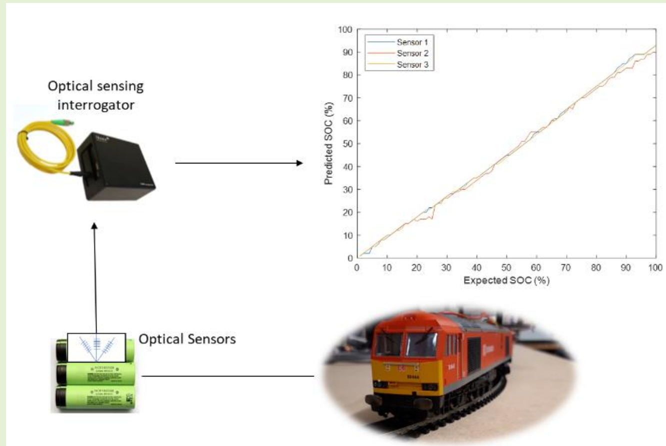
Lithium-Ion battery state-of-charge estimator based on FBG-based strain sensor and employing machine learning

Bruno Rente, Matthias Fabian, Miodrag Vidakovic, Xuan Liu, Xiang Li, Kang Li, Tong Sun, and Kenneth T. V. Grattan

Abstract— **A real-time state-of-charge (SOC) estimator based on the signals obtained from a Fibre Bragg Grating (FBG)-based sensor system is reported. The estimator has used a dynamic time-warping algorithm to determine the best fit, employing previously obtained experimental data. The strain data used were obtained from the optical signal monitored, providing the input to a supervised learning algorithm. The results achieved show a good match with those from conventional techniques, achieving a ~2% accuracy with a ~1% SOC resolution. The system has been successfully applied to a 'proof of concept' demonstrator, using a battery-operated train, illustrating as a result the way in which the real-time SOC estimator could be employed to enhance safety in the growing electrical vehicle industry.**



***Index Terms*— Fiber Bragg Grating, strain sensor, state-of-charge estimation, dynamic time warping.**

I. Introduction

LITHIUM-ION (Li-Ion) batteries are preferred for most of today's energy storage applications, given their favorable power and energy density characteristics. This makes Li-Ion batteries *the* energy storage medium of choice for the electrical-vehicle industry, in its search for optimum performance, including high capacity and high peak power [1].

Despite all the advantages seen in using Li-Ion batteries over other energy storage technologies, there are still clear limitations on their use, which are mainly related to their safety and the optimization of the battery lifespan and capacity. For this reason, a number of studies involving better modelling of key Li-Ion battery parameters have been carried out, to achieve a better understanding of the dynamics of their chemistry in order to maximize their performance, while not compromising the safety of their operation.

State-of-charge (SOC) is one such vital parameter to be monitored for this type of battery, as it can lead to important information about energy optimization and battery stability, as well as to ensure safety of operation. The main techniques employed for SOC estimation use measurements of the key electrical parameters of the battery, including coulomb counting and the Open Circuit Voltage (OCV). Electro-chemical dynamic models can also be created with these parameters and thus used to characterize the state of the battery [1]. However, the complexity of such models brings challenges, such as how to achieve a good estimate of the SOC, without compromising the practicality of the system in which the battery is used.

There are important limitations seen on the practicality of the electrical measurements previously discussed – for example, the Coulomb Counting Technique has serious issues with drift, even with attempts made to realize a dynamic recalibration [2]. On the other hand, the OCV method is clearly not suitable for in-the-field applications, as the battery needs to be 'rested' (or at least charged using very low current rates) before any measurement takes place.

Fiber optic sensors have been shown to be an important technology which can serve as the basis of innovative sensing methods for the development of new models and thus better 'real-time' monitoring, including Li-Ion batteries. Such fiber optic sensors are well suited to use with electrical or battery systems: they are insulating in nature, will not cause short circuiting and are unaffected by electromagnetic compatibility issues, as well as being lightweight and easy to multiplex, as needed. Looking in more detail at optical fiber-based methods,

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Fiber Bragg gratings (FBGs) have been shown to be capable of measuring both surface strain [3] and temperature [4] in these sorts of batteries. Several different types of battery ‘packages’ have been studied for this purpose, including coin cells [5,6], pouch cells [7-9] and cylindrical cells [10]. The fiber optic sensing approach has thus previously been shown to offer important advantages when compared to the use of conventional electrical sensors [9]. Efforts to integrate sensors *inside* the battery cell have also shown satisfactory results for the better thermal modeling of the internal behavior of Li-Ion batteries [10]. However, this option is only feasible as an *aid to modeling and characterization* in the laboratory context, as the battery would then not conform to industry standards (rendering it not suitable for use in ‘real world’ applications).

There is a consensus in the community that the lithiation/delithiation processes cause stresses within the crystalline structure of the battery which, along with thermal stresses seen, will result in losses of the battery capacity [11], which is highly undesirable. Therefore, adequate temperature and strain measurements are vital for the better understanding of the battery fundamentals underpinning the critical charging/discharging of Li-Ion batteries needed for their routine use in many different applications today.

Prior work by Ganguli [12] has used FBG-based sensors in an effort to assess some of the important characteristics of the battery *in use*, such as the SOC. In that research, the data were subjected to Kalman-filtering using an empirical electrical battery model. However, despite achieving good estimations of the SOC, the approach still relies on modeling as the initial point of the study.

As it can be seen from an overview of the literature discussed in this Introduction [1 – 12], FBG-based technology has been employed in different ways over the last five years. This has taken advantage of the capability that such devices have for measuring the two most important parameters for the characterization of the lithiation process, namely temperature and strain – and monitoring these together, for example where strain and temperature changes occur simultaneously. The sensing of the strain in such batteries in use is particularly important as it tends to be directly related to the chemical reaction inside the cells. Monitoring temperature allows tackling one of the most common cause of failure: thermal runaway [13] – and thus before major damage occurs. Apart from using these FBG-based methods, there are few others that can be employed – for example measuring the refractive index inside the battery, obtained using evanescent wave-based sensors [14] or fluorescence-based fiber optic sensors [15]: however, they have not been demonstrated for in-field applications, as yet.

The dynamic time warping (DTW) technique has also been utilized by some researchers, typically to normalize the cycling curve to deal with dynamic current charging/discharging rates. The approach in the work herein is different from what has gone before – its aim is to make use of a DTW algorithm which would then allow an analysis of the strain data obtained from the battery and thus allow a correlation of the outcome of the measurements directly with the battery conditions – a step forward from previous studies. In the demonstration carried out in this work, this has been applied to both an automated cycling potentiostat-based instrument and an electric-train demonstrator, with useful results reported and discussed.

II. SENSOR DESIGN AND TEST SYSTEM SETUP

The Li-Ion batteries used in this work were 3.2 V, 1.6 Ah, cylindrical LiFePO4 cells and as can be seen from Fig. 1, four such cells were used in the experiment carried out. They are Li-Ion batteries broadely typical of those used in industry, including electrical vehicles, as their chemistry is stable enough to be more reliable and safer than other Li-Ion chemistries. As shown in Figure 1, each battery was instrumented with 3 FBG-based sensors glued onto the 18650 cylindrical cell surface. They are co-located within a small footprint, but each with a slightly different orientation. The sensors were attached to the battery package as they were supplied, meaning there were minimal changes to the original packaging, including the non-removal of the polymeric cover (blue plastic shown in Fig. 1). This means that the batteries were not ‘damaged’ by the inclusion of the sensor systems, an important safety consideration. Prior tests carried out showed there were no significant differences when comparing data gathered with or without this battery cover. In this way, the sensors used could be retrofitted easily to the original packaging, with no problems due to potential short-circuit hazards that could arise from interfering with the manufacturer’s original packaging.

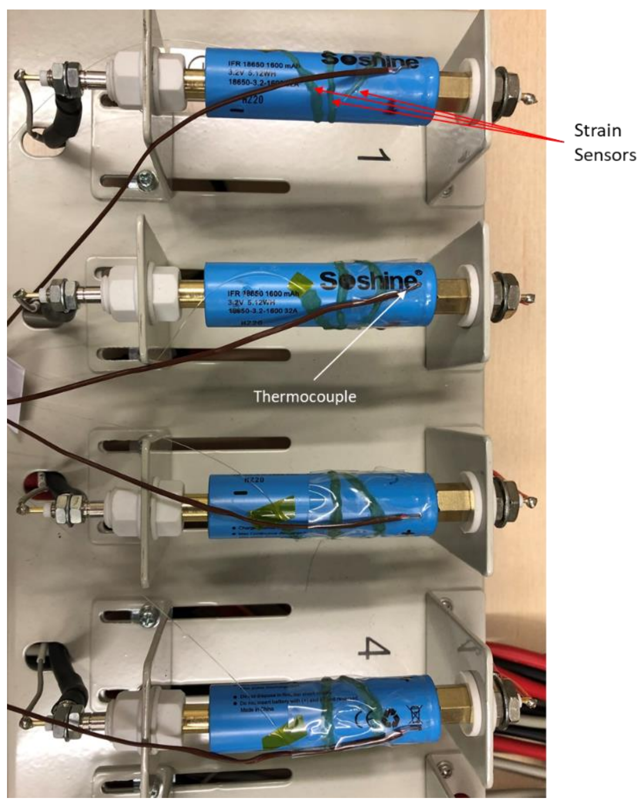

Fig. 1. Battery cycling setup used, illustrating the embedded FBG-based strain sensors.

The principle of operation of the FBG-based sensors is well known (described in prior work by some of the authors [16]). Thus the FBGs used as the basis of the temperature/strain sensors were manufactured using the phase mask method and inscribed in photosensitive fibres supplied by Fibercore (PS1250/1500), using ultraviolet light from a high power KrF excimer laser. The active section of each sensor has a length of 3 mm, a value sufficiently small for ease of glueing on a cylindrical shape, as well as to maintain temperature constancy in the calibration. Each triplet of sensors was attached to each battery after being pre-strained, in order to achieve a linear response through tension and compression excursions. After the sensors were mounted and pre-strained, their characteristic wavelengths were 1534 nm, 1539 nm and 1544 nm, allowing a very confortable excursion as the peak wavelengths of the sensors are 5 nm apart. The FBG-based measurements from the sensors used were performed using a Micron-Optics SM-130 interrogator, operating at 1 kHz for the CC-CV cycling experiment and with Ibsen Optical Monitor for the model-train experiment carried out.

The sensitivities to temperature and strain of the FBG-based devoces used were, on average 14 pm/°C and 1 pm/με for the bare fibers, the former increasing to 21 pm/°C when they were attached to the batteries, after they were pre-strained and the glue was fully cured. Fig. 2 shows typical spectra from both: the fiber attached to the battery and the bare fiber before its attachment, showing that the pre-strain causes an approximately 1 nm wavelength shift.

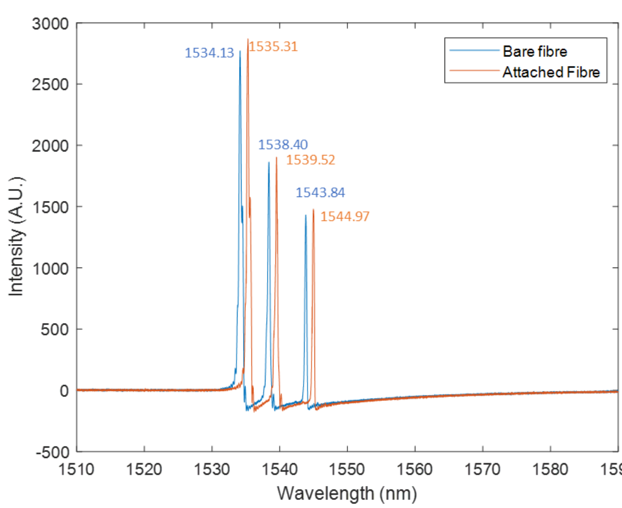

Fig. 2. Spectra of the fiber sensors before and after the pre-straining and following attachment to the battery's cell body.

This sensitivity difference between the response to strain and temperatures experienced means that the strain changes could easily be hidden by the temperature change effect. However, using this sensor layout here, the approach taken allows the discrimination of the strain measurement in the radial direction, by canceling the temperature and longitudinal strain, given the differences in their orientations. Thus as the FBGs respond both to strain and temperature, the wavelength data from the three FBGs that form the basis of the sensor system and that are attached to the surface of the cells were used to calculate the radial strain information. As the sensors are placed at a known angle in respect with each other, temperature discrimination can be achieved by using the method described by Pereira *et al* [17]. As the radial strain is of interest and the sensors were small and sufficiently close to each other, the temperature compensated measurement of the radial strain (ε_r) can be derived from the following relationship:

$$\varepsilon_r = \frac{\left(\frac{\Delta\lambda_1}{\lambda_1} - \frac{\Delta\lambda_2}{\lambda_2}\right)}{(1-p_e)-(1-\cos(\theta)^2)} \quad (1)$$

where p_e is the photo-elastic coeficient of silica, λ_1 and λ_2 are the Bragg wavelengths for each sensor and θ the angle between them. As there are three sensors, the response of the combination of pairs was averaged to achieve a more stable compensation. The resulting calibration was tested in a stable chamber, using co-located thermocouples and conventional strain gauges as a reference, to ensure the system, worked well.

In order to create an effective comparison of the performance of the system developed with that of well-established methods for SOC estimation, a constant-current/constant-voltage (CC-CV) procedure was adopted for the battery charging following a CC discharge. In addition to the use of the FBG-based sensor system monitoring, the cell current (Coulomb Counting) and voltage were also recorded.

Figure 3 shows the clear correlation between the strain measured from each battery (using the FBG sensors) and its SOC calculated using Coulomb Counting, when they were subjected to a series of charge/discharge cycles, performed at a rate of 1C, using a potentiostat.

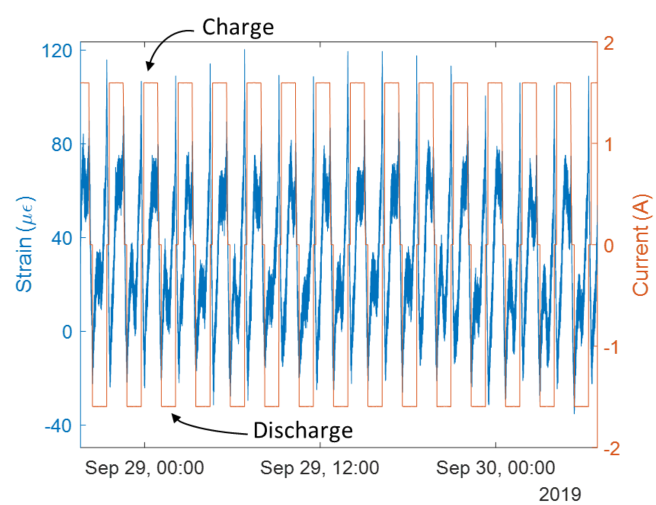

Fig. 3. Illustration of CC-CV charges and CC discharges (orange) along with the FBG strain response (blue).

Using the above, the system was evaluated in a convenient laboratory-based environment (which satisfactorily mimics 'real world' use) and consisting of a model train circuit assembly to simulate the operation of a battery-operated vehicle in normal use. This experiment allows tackling one of the bigger issues arising from the discussion presented in the Introduction: the lack of tests performed under conditons where there are uncertainties inevitably present in field applications, such as in an electrical vehicle. To look at this closely, the demonstrator was run under several different conditions: of temperature, random noise and unknown initial SOC, as the start/stop runs are not as precise as is the potentiostat experiment.

A portable interrogator from Ibsen Photonics was used in conjunction with a Raspberry-Pi processor for the data acquisition (as illustrated in Fig. 4). Here a 3-cell battery pack was used (which was appropriate to the train-based simulation undertaken here) and again, current and voltage were measured for the Coulomb-Counting comparison (as well as to ensure safety in the experimental setup). For each discharge cycle, the train was continuously operated, until the voltage reached a safe minimum of 8 V.

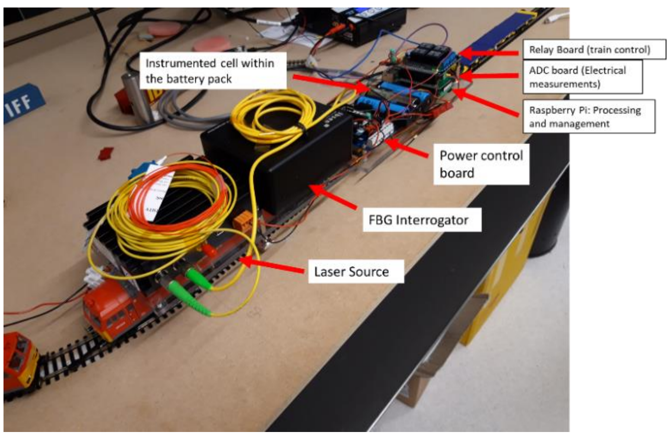

Fig. 4. Instrumented battery-operated demonstrator train.

Following the acquisition of the cycling data obtained from both the potentiostat and the model-train runs undertaken, the dynamic time warping (DTW) method was used to evaluate the strain data obtained from the optical sensors and to establish the correlation of the strain with the SOC of the cells.

DTW is a method widely used to recognize patterns in time-series data, used in speech recognition and other waveforms in discrete time series. The method is based on the calculation of the minimum warping path that a sampled set of data needs to fit a model set, i.e. the algorithm calculates the minimum 'distance' that is required to transform one set of data into a previously stored one [18].

The DTW method is then used to calculate the 'cost function' of the comparison between two signals and thus to identify the 'least costly' warping path. A matrix with the two signals is created (an N by M matrix) where N and M are the lengths of the two time series, obtained from the testing and the comparison series respectively. Each element, $d_{i,j}$, in this matrix will be equivalent to the Euclidean distance between the values x_i from the testing series and y_i (where i,j = 1,2,3…) from the comparison series, using the relationship:

$$d_{i,j} = |x_i - y_j|, \forall ij \qquad (2)$$

The rationale used in this work is that the 'cost' between the strain data being measured will be a minimum when compared to a fraction of the entire cycle (with this cycle having been calibrated against its associated SOC). For instance, if the cell is at 50% SOC, the distance will be minimal when the comparison is made against half of the charging graph (and higher at other values). The minimum distance is achieved by the use of the nearest-neigbour classifier method.

III. SOC Evaluation Using Strain Data

As discussed earlier, the Li-Ion intercalation will cause stresses on the battery. However, the whole effect of strain will occur at the anode due to the swelling of the graphitic structure used [19]. Those strain data were then used in this work for the characterization of the battery SOC. Despite the fact that the strain data were likely to be valuable to reflect the battery state, the chemistry and geomectric complexity associated would be expected to show non-linear behaviour, as shown in the 2 cycles of charging/discharging illustrated in Fig. 5 - the data were obtained from a potentiostat.

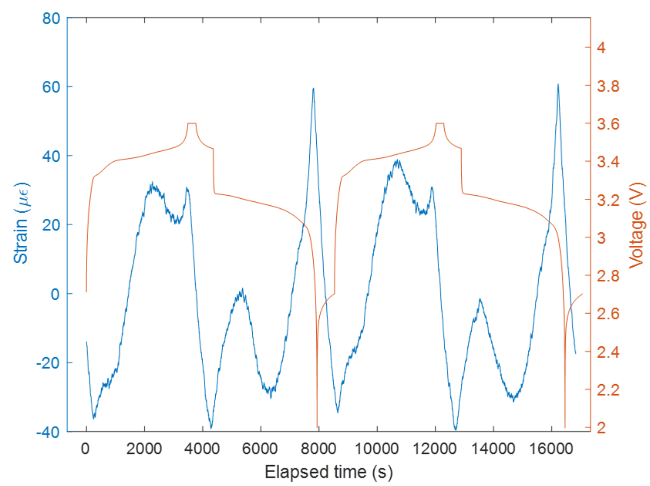

Fig. 5. FBG data from two subsequent CC/CV charging/discharging cycles at 1C rate.

It can be seen that the cyclical data obtained were very reproducible and that the charging/discharging processes are easily distinguisible: however, the SOC is not a simple polynomial function of the strain. Therefore, a DTW algorithm was implemented as a means to predict the SOC, instead of creating a simple fitting of the data.

The DTW algorithm created for this application was developed using two aproaches and their performance compared. It should be noted that: (1) the whole strain dataset from the beginning of its charging or discharging process was compared to parts of the training data, similar to that shown in Fig. 5. The key similarity, i.e. the minimum Euclidean distance between the two datasets, will be a maximum when it is indicated that the batteries have the same capacity. Further: (2)

fractions of the strain data set were compared with the training data, as by doing so, the outcome expected would be an increase of the computational performance (as the data set size for DTW decreases), thus avoiding the need to know accurately the point where the cycling begins and ends. The drawback in this case is a loss in accuracy, as the smaller dataset will be less identifiable for use with the algorithm. Fig. 6 shows the prediction of a charging cycle using the DTW algorithm on the FBG-based sensor strain data for the latter aproach, as its superior performance has shown it to be more compatible to that for the desired application. The resolution was fixed at 1% SOC. The expected SOC is the value of the reference used for training the dataset. In this case, the reference used was the data acquired by the Coulomb Counting method. Despite this method is being used for this demonstration in this work, any reference method could be used instead: this being the optimal case of a mix of methods with models, as described in the Introduction.

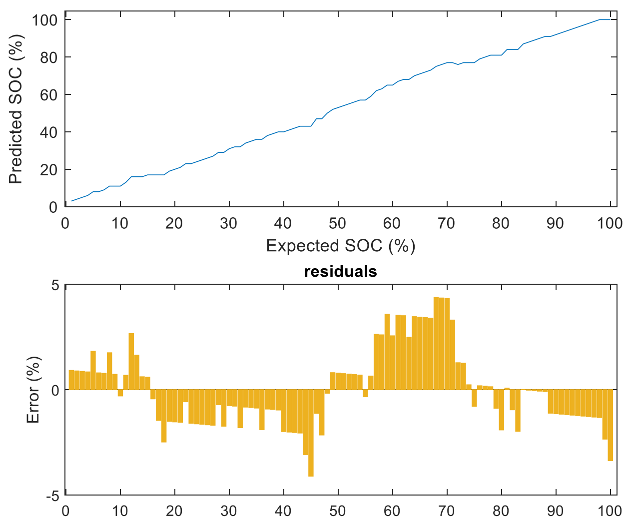

Fig. 6. Prediction of the SOC using DTW algorithm on the FBG strain data and residuals comparing to the optimum prediction.

The result obtained for the prediction of the SOC showed that the maximum values of the residuals always are <5% for all cases when the method discussed is used (when comparing to the expected values). The figures are very similar for both charging to discharging, although some differences arise from the fact that the curves shapes are not the same and thus the DTW performance will likely be so as well. It is worth noting that the algorithm will fail if the graph has long periods of ‘steady’ behaviour, as its shape will not differ across the different time intervals studied. Moreover, this method was tested in this work for the $LiFePO_4$ chemistry of Li-Ion battery only. For chemistries other than that mentioned, it is likely that the shape of the graph will be completely different: thus the DTW will fail to find similarities. The training data used thus must be obtained from batteries of the same type, as was done for the sample used in the testing here.

Focusing on the main goal of this project, the same approach was implemented on a further model train demonstrator and in this case, additional challenges were seen. The demonstrator has been designed to be as close as possible to the situation seen for a real, full-sized electric train (and be fully representative, even though it is a model). Therefore, it reflects the situation with the full-sized train, where errors caused by environmental factors such as temperature variations and deviations on the current rate of charging and discharging will be seen. One important factor to be considered is that the charging process needs to be carried out with the train system (instruments and power management) operating. The test train itself drains roughly 400 mA from the three-battery pack (9 V), while the instruments attached to it drain 800 mA. Therefore, the charging curve will be flattened, as shown in the example seen in Fig. 7 for each cycle. In this graph, the discharging process lasts for one hour while the charging cycle lasts three times longer than that, as the power consumption is two thirds of the battery charging rate. Despite the larger errors involved on the cycling dynamic, the data are still reproducible, so the DTW algorithm can be applied using the same approach as with the potentiostat cycling data. Another interesting observation from this graph is that despite the same discharge rate (1C) being used, the shape of the graph showing the strain changes is very different, suggesting that the nature of the load will affect the strain caused to the battery. While the load is totally resistive in the potentiostat case, it is mainly inductive in the demonstrator.

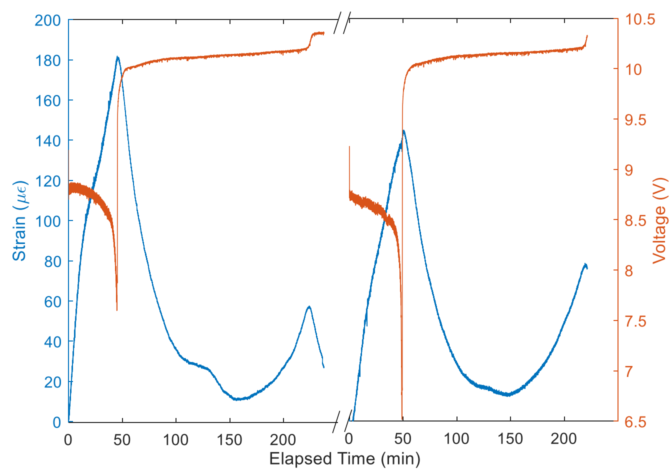

Fig. 7. Strain data from two different cycles of the train demonstrator operation and the voltage for the cell during each of the experiments.

Another very important parameter that can be determined from analysis of the same data (as discussed above), is the temperature shift. Despite the environment temperature being kept constant, there is a temperature shift that is related to the charging and discharging processes through the nature of the reaction experienced. It is important to observe that behaviour, as shown in Fig. 8.

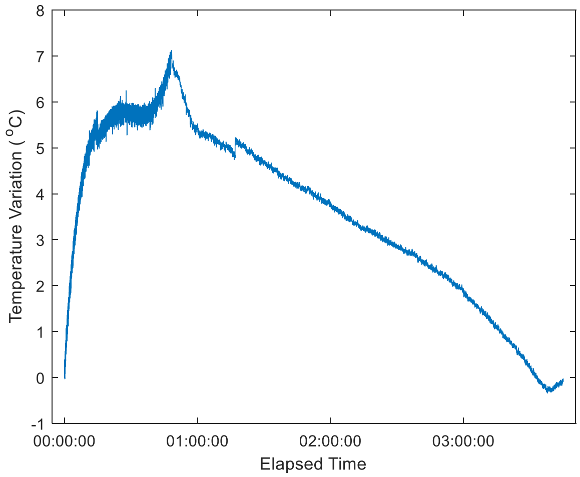

Fig. 8. Temperature variation data obtained from one cycle of the demonstrator use.

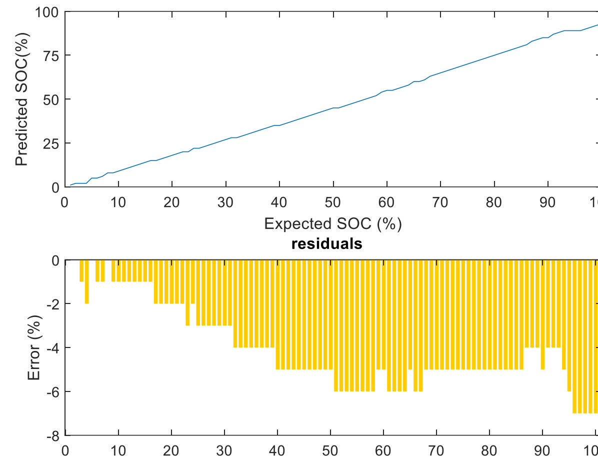

Fig. 9. SOC prediction using the demonstrator train datasets and residuals for comparison to the optimum prediction.

The temperature is seen to follow the strain behaviour and increase during discharge, as expected. However, it is clear from Fig. 7 that the second half of the discharging process generates more significant changes in strain than are seen in the temperature. The same effect occurs for the charging process, as the temperature changes are less abrupt than the strain. This kind of result can benefit the development of better models for the electro-chemical characterization of the batteries. Another potential outcome from the temperature measurements is that they can be used in the same way (as the strain data) to increase the accuracy of the predictions. However, this is beyond the scope of this study (and will be discussed in subsequent work).

Fig. 9 shows the results of the use of the predictive algorithm employing the data generated from the various cycles of the demonstrator model train considered. In this case, the prediction results show higher errors than were seen for the potentiostat measurements, possibly because of random variations of current rate, compared with the controlled environment of the potentiostat. The predicted SOC (solid - blue curve) deviates slightly from the optimum fit (dashed - red curve) when the SOC approaches 100%. This can indicate that the battery state of health (SOH) is not the same as the training data, which could be used in a future SOH estimator and be corrected by this. The observed error is still ~5%, even in these cases.

As shown in the SOC prediction illustrated in Fig. 9, the performance of all three sensors was very satisfactory and a close correlation with the training data was achieved. The algorithm contains some adjustment parameters, on which the quality of the results will depend. The most important parameter is the SOC resolution, which was set to 1% throughout this investigation. The testing window, i.e., the size of the data set to be compared, will directly affect the accuracy of the prediction. The larger the datasets, the better will be the correlation with the training data and thus the confidence that the minimum Euclidean distance will reflect well the correlation. Another parameter which must be set is the number of training cycles to be used on the comparison. The number of cycles chosen is a balance: it must be high enough to deal with random fluctuations on the data but not large enough to increase the computational cost to the point where the method becomes impractical. The DTW function is the most computationally costly of all the parts of the algorithm and must therefore be carefully adjusted, if implemented in a real-time system. Fig. 10 shows an example of an experimental run with the real time estimator and its comparison with the approach of the Coulomb Counting method.

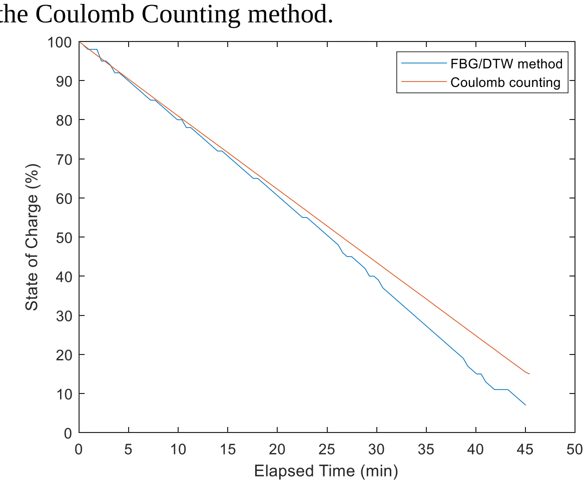

Fig. 10. Real time comparison between the proposed method and a Coulomb counter for the train demonstrator.

This experiment uses the DTW algorithm which was previously evaluated, in terms of its characteristics such as resolution and training data size, as well as for errors it demonstrated through the residual graphs in this paper. It has been applied for each data point during the entire run, having thus one predicted point every 30 seconds. The computational cost showed this to be sufficiently small for this application, demonstrating that even more sophisticated algorithms could be run in such a system, in real time. The SOC errors associated with the prediction was indeed as was expected, having higher errors compared to the Coulomb Counting approach on the second of the runs carried out, as shown in the residuals in the graph in Fig. 9.

All the SOC curves, obtained in this work and from any one of the several cells tested, are essentially similar, so the DTW algorithm can be used to compare one cell against any other. Thus, conveniently, a user could select a brand new battery and use the training information obtained from the old batteries that had previously been evaluated. Thus the results obtained are representative from all cells but yet come from a random cycle, from one cell only.

IV. Discussion

The work undertaken has shown clearly that a simple machine-learning algorithm based on DTW can be used to evaluate the SOC of representative Li-Ion batteries, using fibre-optic sensors which are highly compatible with installation on such battery systems. The FBG-based sensor data obtained were shown to be reliable and sufficiently reproducible to serve as the input for the DTW algorithm used.

A resolution of 1% SOC was achieved with an accuracy of better than 5% in all cases, and even better than 2% in certain particular situations. The accuracy figure has been shown to be highly dependent on the data behaviour, as better results were achieved when data show sufficient variation in time. This characteristic arises from the nature of the DTW method and can be mitigated with the use of other methods in parallel, such as Kalman filtering or neural networks, using the same data as input.

The fact that the sensors are surface mounted on the battery rather than being embedded *inside* the cells, illustrates that this is a feasible approach to creating a novel, cost-effective, non-invasive method for SOC prediction. Therefore, the system has been shown to be ready for applications to safety-sensitive environments, such as industries where Li-Ion batteries are currently used. Recognizing the predicted growth of Li-Ion batteries in automotive and rail transport, as well as wider potential applications of Li-Ion batteries across a range of sectors, emphasizes the value of the approach demonstrated.

The use of the model train has proved to be very effective for this proof-of-concept study for future battery management systems, especially in electrical vehicles. The system behaviour was shown to be reliable and indeed very satisfactory, operating as it does in real time and can thus such a system can be employed effectively in a variety of 'real-world' electrical vehicle applications.

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References

[1] J. Zhang, and J. Lee, "A review on prognostics and health monitoring of Li-ion battery," *J. Power* Sources, vol. 15, 6007-6014, Aug 2011.

[2] K. S. Ng, C.-S. Moo, Y.-P. Chen, Y.-C. Hsieh, "Enhanced coulomb counting method for estimating state-of- charge and state-of-health of lithium-ion batteries," *Appl. Energy*, vol. 86, no 9, 1506-1511, Sep 2009.

[3] C. J. Bae, A. Manandhar, P. Kiesel, and A. Raghavan, "Monitoring the Strain Evolution of Lithium-ion Battery Electrodes using an Optical Fiber Bragg Grating Sensor," *Energy Technology*, vol. 4, 851-855, Mar 2016.

[4] S. Novais, M. Nascimento, l. Grande, M. F. Domingues, P. Antunes, N. Alberto, C. Leitao, R. Oliveira, S. Koch, G. T. Kim, S. Passerini, and J. Pinto, "Internal and External Temperature Monitoring of a Li-Ion Battery with Fiber Bragg Grating Sensors," *Sensors*, vol. 16, 1394-1403, Aug 2016.

[5] G. Yang, C. Leitão, Y. Lib, J. Pinto, and X. Jiang, "Real-time temperature measurement with fiber Bragg sensors in lithium batteries for safety usage," *Measurement*, vol. 46, 3166–3172, 2013.

[6] A. Fortier, M. Tsao, N.D. Williard, Y. Xing, and M.G. Pecht, "Preliminary study on integration of fiber optic Bragg grating sensors in li-ion batteries and in situ strain and temperature monitoring of battery cells," *Energies*, vol 10, no. 7, 838, May 2017.

[7] L. W. Sommer, P. Kiesel, A. Ganguli, A. Lochbaum, B. Saha, J. Schwartz, C. J. Bae, M. Alamgir, A. Raghavan, "Fast and slow ion diffusion processes in lithium ion pouch cells during cycling observed with fiber optic strain sensors," *Journal of Power Sources* ,Vol. 296, 46-52, Jul 2015.

[8] A. Raghavan, P. Kiesel, L. W. Sommer, J. Schwartz, A. Lochbaum, A. Hegyi, A. Schuh, K. Arakaki, B. Saha, A. Ganguli, K. H. Kim, C. Kim, H. J. Hah, S. Kim, G. O. Hwang, G. C. Chung, B. Choi, and M. Alamgir "Embedded fiber-optic sensing for accurate internal monitoring of cell state in advanced battery management systems part 1: Cell embedding method and performance," *Journal of Power Sources*, vol. 341, 466-473, Feb 2017.

[9] M. Nascimento, M. S. Ferreira, and J. L. Pinto, "Real time thermal monitoring of lithium batteries with fiber sensors and thermocouples: A comparative study," *Measurement*, vol. 111, 260-263, Dec 2017.

[10] J. Fleming, T. Amietszajew, E. McTurk, D. Greenwood, and R. Bhagat, "Development and evaluation of insitu instrumentation for cylindrical Li-ion cells using fibre optic sensors," *HardwareX*, vol.3, 100-109, Apr 2018.

[11] C. ChiuHuang and H. S. Huang, "Stress Evolution on the Phase Boundary in $LiFePO_4$ Particles," *Journal of The Electrochemical Society*, vol. 160, no. 11, A2184-A2188, Oct 2013.

[12] A. Ganguli, B. Saha, A. Raghavan, P. Kiesel, K. Arakaki, A. Schuh, J. Schwartz, A. Hegyi, L. W. Sommer, A. Lochbaum, S. Sahu, M. Alamgir, "Embedded fiber-optic sensing for accurate internal monitoring of cell state in advanced battery management systems part 2: Internal cell signals and utility for state estimation," *Journal of Power Sources*, vol. 341, 474-482, Feb 2017.

[13] S. Koch, K.P. Birke, and R. Kuhn, "Fast Thermal Runaway Detection for Lithium-Ion Cells in Large Scale Traction Batteries," *Batteries*, vol. 4, no. 16, Mar 2018.

[14] A. Ghannoum, P. Nieva, A. Yu, and A. Khajepour, "Development of Embedded Fiber-Optic Evanescent Wave Sensors for Optical Characterization of Graphite Anodes in Lithium-Ion Batteries," *ACS Applied Materials & Interfaces*, vol. 9, no. 47, 41284-412902017, Nov 2017.

[15] W. Qin, S. O. Obare, C. J. Murphy, and S. M. Angel, "A fiber-optic fluorescence sensor for lithium ion in acetonitrile," *Analytical chemistry*, vol. 74, no. 18, 4757-4762, Aug 2002.

[16] F. Surre, T. Sun and K. T. Grattan, "Fiber Optic Strain Monitoring for Long-Term Evaluation of a Concrete Footbridge Under Extended Test Conditions," *IEEE Sensors Journal*, vol. 13, no. 3, 1036-1043, Mar 2013.

[17] G. Pereira, M. McGugan, L. P. and Mikkelsen, "Method for independent strain and temperature measurement in polymeric tensile test specimen using embedded FBG sensors," *Polymer Testing*, vol. 50, 125-134, Apr 2016.
[18] D. J. Berndt and J. Clifford, "Using dynamic time warping to find patterns in time series," *KDD workshop*, vol. 10, no. 16, 359-370, July 1994.
[19] N. Zhang, H. Tang, "Dissecting anode swelling in commercial lithium-ion batteries," *Journal of Power Sources*, vol. 218, no. 15, 52-55, Jul 2012.

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